Joint AIAA-SIAM Sessions on Managing Uncertainties in Cyber-Physical-Human Decision-Making

- Why / What
  - Call AIAA audience's attention to the Society for Industrial and Applied Mathematics (SIAM), with which AIAA domains share much in common.
  - Discuss problems, applications, methodologies in managing uncertainties in H-M teams.
  - Major focus on machine-related uncertainties, as they impact the entire CPH system.
- Session 1 speakers:
  - Danette Allen , NASA
  - Cody Fleming, Iowa State (two presentations)
  - Melkior Ornik, UIUC
- Session 2 speakers:
  - Javier Puig-Navarro, AMA
  - John Pye, U. Michigan and NASA
  - Natalia Alexandrov, NASA
  - Anirban Chaudhuri, UT Austin

Authority in Human-Machine Teams as a Function of Problem Complexity

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2024 SciTech Forum, 8-12 January

Orlando FL

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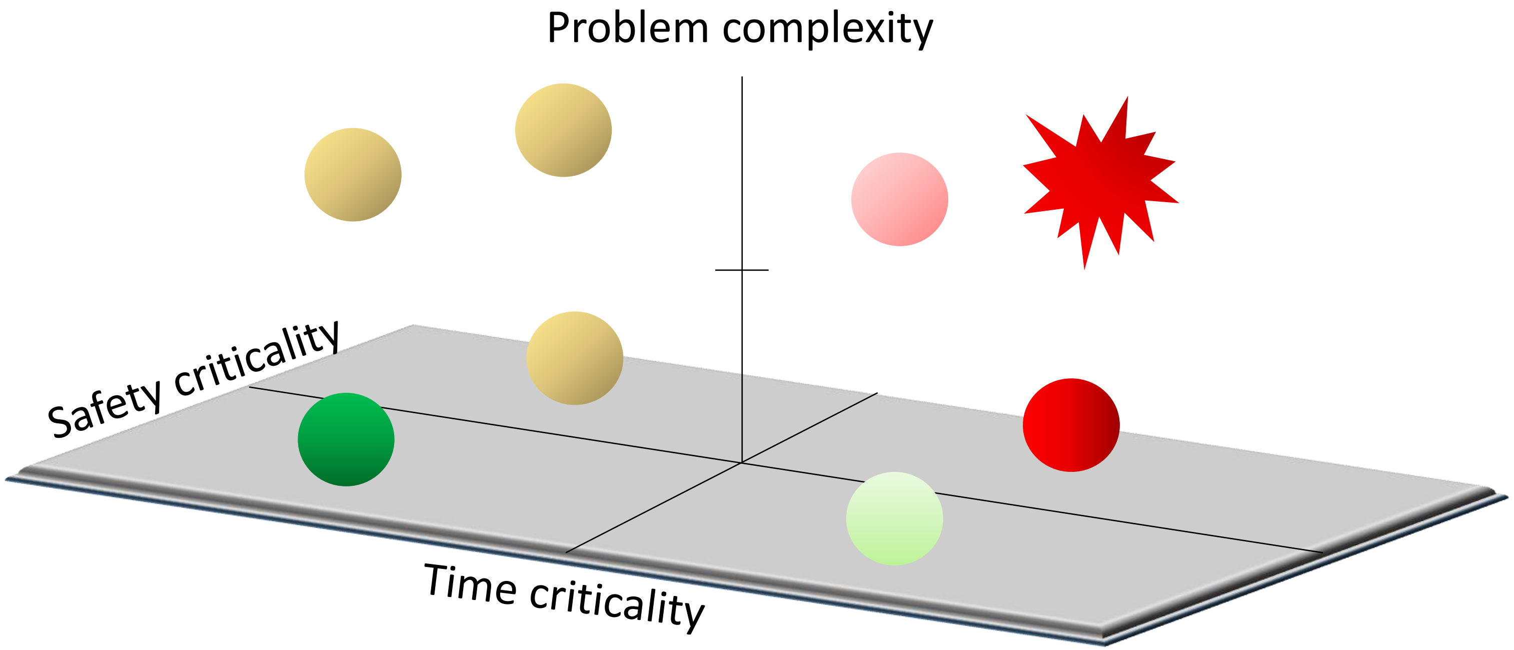
Problem Setting

- H-M teaming is a vast and open area, rich with uncertainties.
- Commonly expressed sentiment:
  - “Let humans do what they do best, and machines do what they do best”.
  - Works for well-defined environments.
  - Ultimate decision-maker is assigned *a priori*.
- Facts:
  - In new environments, decision-making capabilities and needs may change in real time.
  - A single decision precedes ∀ action.
  - Strictly rule-based behavior may be fragile.
- Q: In a dynamic environment, which agent to trust with a specific decision?
- Working hypothesis: formal representation of H-M decision-making supports reasoning about the system and reduces uncertainty in outcomes.

Effects of Decision Domain Attributes



- Low time-criticality allows for deliberation and negotiation among solutions.
- Low (context-dependent) complexity allows for *a priori* authority selection.
- High time criticality and high complexity require <u>*a priori* trust</u> or ensuring <u>reliable computation in real time</u>.
- Claim: formal problem representation needed in time-critical, safety-critical, and high-complexity domains.

A Critical Aspect of Uncertainty

- In any system that involves decision-making: the ability of agents to arrive at satisfactory decisions and the attendant actions in time, as a function of problem complexity.
- Reducing solvability uncertainty is always done via bounding problem complexity; e.g., current airspace.

General Idea

- Represent problem complexity in a computable, actionable form.
- Build models of problem solution behaviors as a function of problem complexity.
- Detect approaches to unacceptable complexity.
- Reconfigure system and/or decision-making; dynamic re-assignment of authority in H-M teams.

Measure of Complexity

- Tractability of the problem solution on a time budget, as a function of external and internal parameters.
- The quality of solutions of the decision-making problem:
  - Constraint satisfaction
  - Distance from optimality
  - Robustness (maximum uncertainty under which performance is guaranteed)
  - Serendipity (minimum uncertainty that would allow for great improvements in performance)
- Other, context-dependent and formulation-dependent functions.

Conceptual Reasoning Framework

Given:

- *An agent and a goal*

Initialize:

- *Set time $t=0$*
- *Set initial sampling time interval Δt*
- *Set initial look-ahead time T*
- *Set initial look-ahead sampling time interval $\Delta\tau$*
- *Select initial problem-solving algorithm P*
- *Select environmental complexity parameters C*
- *Select initial environmental complexity model M*
- *Select transition criteria*
- *Select stopping criteria*

Conceptual Framework, cont.

Do until (stopping criteria are satisfied)

Acquire and assess complexity parameters C at time t

Set $\tau = t$

Do while ($\tau \leq t + T$)

Estimate look-ahead complexity parameters at time τ

$\tau = \tau + \Delta\tau$

End do

Input complexity parameters into complexity model M; assess approach to phase transition

If (approach to transition detected) then

Reconfigure operations (add structure ∨ change agent)

Else

Assess system's performance slack

If (slack)

Reconfigure operations (relax structure ∨ change agent)

Else

Continue present operations

End if

End if

Update time

End do

Example: *ab initio* air traffic control

Problem:

- Agent computes trajectory of an aircraft from point A to point B.
- No assumption on structure.

Complexity parameters:

- External:
  - Density and heterogeneity of the relevant airspace volume.
  - Interaction activation
- Internal, e.g.: physical properties of the aircraft.

Tractability:

- Solving trajectory optimization problem on a time budget.

Metrics for quality of solutions of the decision-making problem:

- Constraint satisfaction.
- Optimality.
- Robustness: robust solutions live in the regions of space that allow for many alternative solutions (e.g., flexibility preservation, Idris et al.).

MAGE (Monitor, Anticipate, Guide, Evolve) for Air Traffic

- Complexity model construction:

Number of aircraft
Aircraft velocities
Decision-making scheme
→
Machine Learning Model
(or Other Data-Fitting Model)
→
Estimate of solution time
Estimate of solution quality

- Reconfiguration: change in the decision problem objectives, constraints, and variables
  - Directed modification
  - Autonomous, distributed modification with emergent outcomes
  - Hybrid directed-autonomous

  - Example: reduce weight of the delay objective in high-risk, dense environment

- Decision-making strategies:
  - Solution strategy (e.g., optimization) affects the outcome of actionable complexity prediction
  - As new capabilities arise, complexity models must be re-calibrated

Preliminary Computational Results

- Operation setup in ATMLG (Air Traffic Monotonic Lagrangian Grid)
  - **Initialize system**
    - N = number of aircraft
    - System aircraft interaction distance (10 mi)
    - Set time t_i = start $time_i$ (can be 0 or chosen randomly from a set) for i=1,…,N
  - **Do ∀ 10 sec until End**
    1. ID all aircraft in conflict (within interaction distance)
    2. For ∀ aircraft in conflict, select: {x_1 = Δ heading±45°, x_2= Δ speed±10 kt, x_3= Δ altitude±1000 ft}
    3. For ∀ pair of aircraft in conflict, formulate a constraint:
       1. Compute t of closest approach for 2 aircraft based on current position, heading and speed (regardless of altitude)
       2. Compute separation distance between the 2 aircraft at t of closest approach
       3. Compute a projected altitude factor

          $f_1 = 1 - \frac{(alt_1 - alt_2)}{Alt_{sep}}$ $\quad$ $f_2 = 1 - \frac{(alt_2 - alt_1)}{Alt_{sep}}$ $\quad$ $g = \left(1 - \frac{distance_{closest}}{distance_{allowed}}\right) * f_1 * f_2$
    4. Solve minimize $\sum \left(\frac{x_i}{scale_i}\right)^2$, subject to $g \leq 0$
  - **End Do**

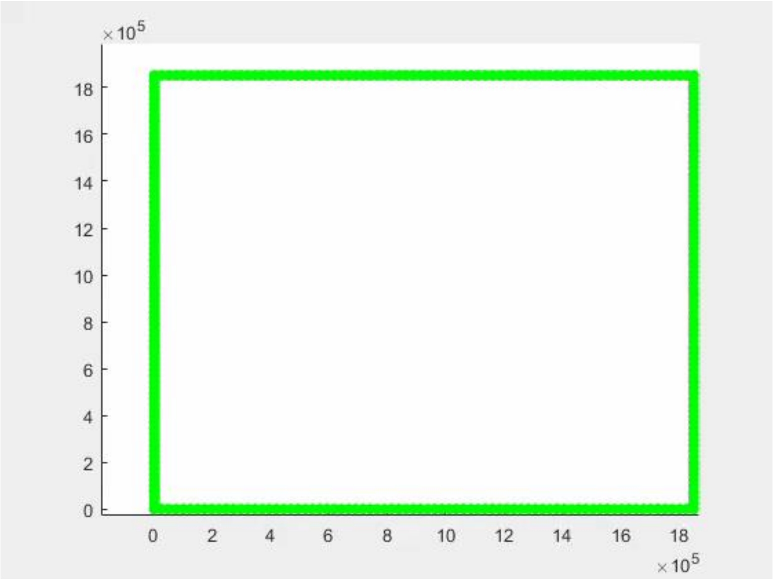
Sample of Outcomes

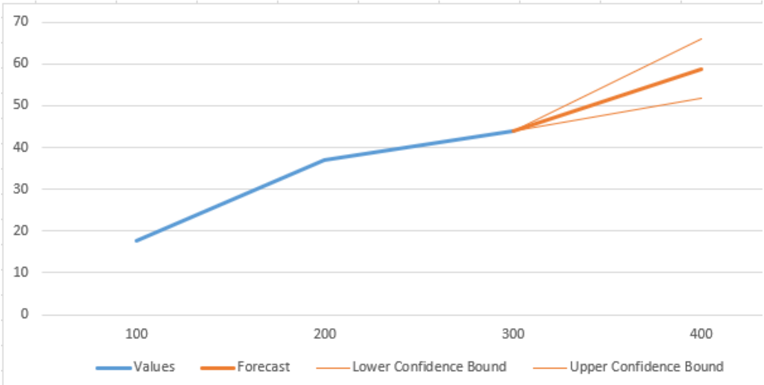
Training set

Validation set

Different optimizer

	A	B	C	D	E	F	G	H	I	J
1	All planes flying at a constant altitude of 30,000 feet.									
2	All planes flying at a constant airspeed of 400 knots.									
3	Check distance is 10 nautical miles and intrusion distance is 5 nautical miles.									
4	Circle radius is 1000 nautical miles.									
5	All planes start at time=0.									
6										
7	Optimizer	number of	initial	trial	number of	number of	closest	execution	optimizer	optimizer
8	name	planes	separation	number	conflicts	course changes	approach	time	total time	worst case time
9	KSOPT	100	62.83	1	118	89	5.00	19.187500	0.026000	0.008000
10		100	62.83	2	118	103	5.00	16.609375	0.055000	0.009000
11		100	62.83	3	98	70	4.50	17.171875	0.012000	0.008000
12		100	62.83	4	134	125	5.00	17.546875	0.038000	0.001000
13		100	62.83	5	126	111	5.00	17.656250	0.016000	0.001000
14		200	31.42	1	500	495	2.50	29.781250	0.261000	0.010000
15		200	31.42	2	482	545	1.70	29.031250	0.193000	0.020000
16		200	31.42	3	410	400	3.60	27.500000	0.232000	0.021000
17		200	31.42	4	508	423	4.60	28.281250	0.215000	0.021000
18		200	31.42	5	446	415	4.20	27.406250	0.259000	0.010000
19		300	20.94	1	1066	1034	1.90	42.968750	2.955000	0.402000
20		300	20.94	2	1064	1083	1.50	44.015625	3.389000	0.419000
21		300	20.94	3	1148	1049	2.60	11.859375	2.359000	0.203000
22		300	20.94	4	1052	1004	2.50	12.968750	3.735000	0.923000
23		300	20.94	5	1072	1058	0.90	13.890625	3.677000	0.616000
24		400	15.71	1	1906	1865	1.10	33.375000	22.192000	2.733000
25		400	15.71	2	1972	1892	0.70	47.406250	34.176000	7.738000
26		400	15.71	3	1910	1781	0.90	30.625000	19.172000	3.087000
27		400	15.71	4	2008	2026	1.30	39.984375	27.847000	4.613000
28		400	15.71	5	1984	1944	1.70	38.609375	26.579000	3.765000
29	NLOPT_MMA	100	62.83	1	84	69	5.00	36.546875	31.311000	12.550000
30		100	62.83	2	100	65	4.30	65.031250	59.835000	12.488000
31		100	62.83	3	82	44	3.60	77.453125	70.474000	11.719000
32		100	62.83	4	118	67	3.10	17.906250	11.362000	3.866000
33		100	62.83	5	114	125	4.60	81.093750	75.586000	10.797000





Timeline	Values	Forecast	Lower Confidence Bound	Upper Confidence Bound
100	17.63438			
200	36.99375			
300	44	44	44.00	44.00
400		58.77883	51.65	65.91
		actual 38.		

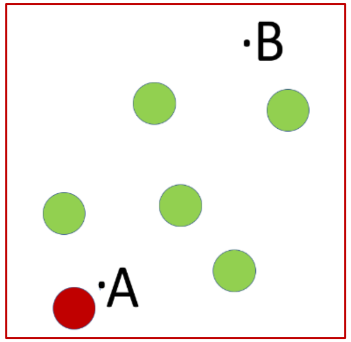
More Numerical Tests of Tractability Prediction

- Shortest Path Finding via Visibility Graph

# obstacles	# scenarios	Avg. # solutions	Avg. time to solution (sec)	# test scenarios	Avg. # test solutions	Avg. % time prediction Δ
4	100	97	0.86	25	24	0.02
5	100	89	1.31	25	19	0.07
10	100	34	324.33	25	7	2.03
20	100	2	4800.00	25	Not found	N/A

- Minimization of Deviation from Optimal Path

# obstacles	# scenarios	Avg. # solutions	Avg. time to solution (sec)	# test scenarios	Avg. # test solutions	Avg. % time prediction Δ
4	100	94	0.38	25	25	0.01
5	100	100	0.37	25	23	0.01
10	100	83	11.60	25	24	0.03
20	100	86	64.52	25	19	0.05



- Detect trends in computational tractability of simple decision problem formulations, using examples of two formulations and two decision-making schemes.
- Results to date indicate that further development of the planned complexity models is justified.

Evaluating Approach

Metrics

- Accurate detection of shifts in tractability and quality of solutions from nominal?
- Clear ID of dependence of precursors (slowing down of solutions, shrinking of feasible regions) as a function of variables?
- Low percentage of false positives?
- Note: Comparative metrics are not available because there is no baseline SOA.

Risks

- In shared-rules approaches, low risk.
- In algorithmic decision-making, the risk of not detecting precursors in time is higher.
- Mitigation: Lack of detectable precursors will point to the need for different control schemes.

Rewards

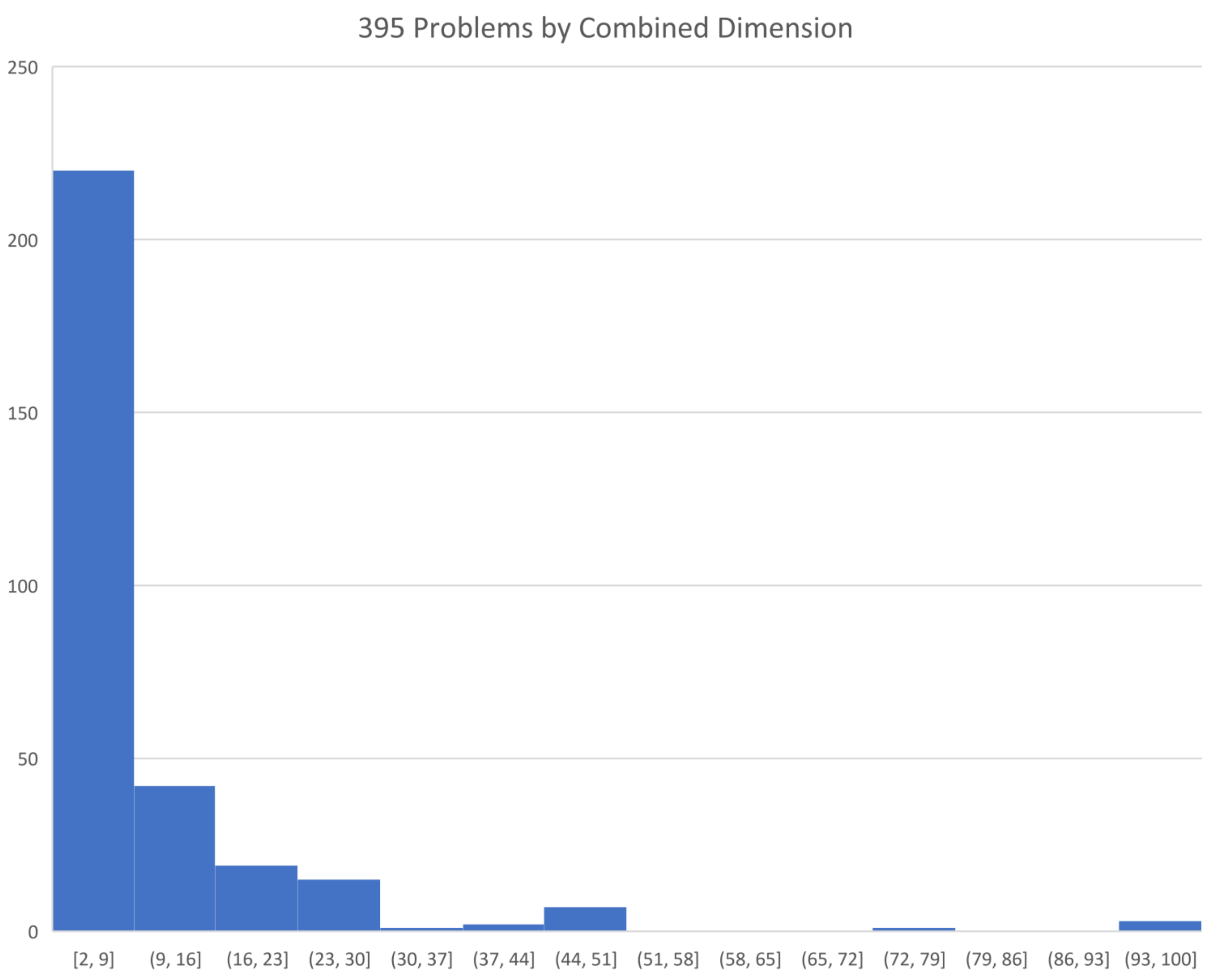
- Insights into practical sensitivities of a dense, heterogeneous system to control strategies and uncertainties.
- A component in a toolbox for monitoring system controllability, efficiency, and safety, regardless of the overall control strategy.

How Would Transfer of Authority Happen?

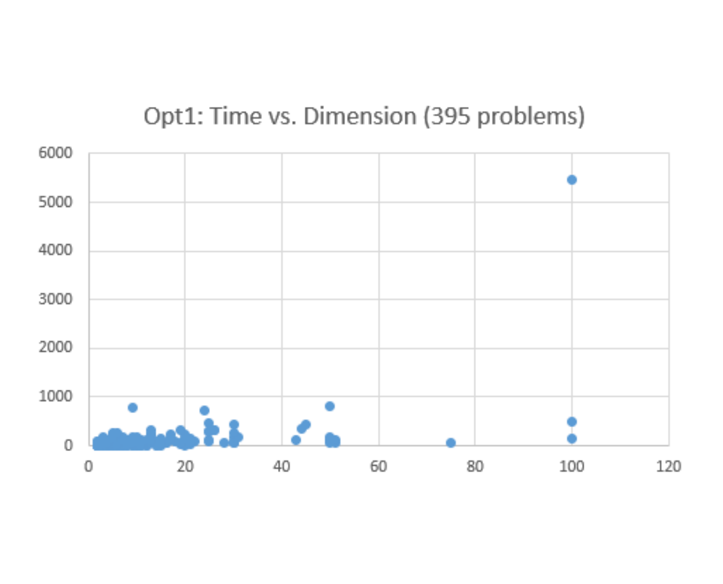
- (After conditioning the system to minimize loss of solvability, uncertainty remains.)
- Given:
  - Agents in an H-M team, Alice, Bob, and Charlie.
  - Alice and Bob propose two actions.
- Q: How should Charlie decide which action to approve, i.e., whom to trust?
- Fact: Proposed actions are results of problem solving by Alice and Bob.
- If all problem objectives and their priorities are well known, comparison of solutions is straightforward. In an H-M team, such knowledge may be limited due to, e.g.:
  - Incomplete problem formulation.
  - Implicit, changing, arising objectives.
  - ML: reward hacking.
- Build a model of trustworthiness (ability to solve problems) as a function of solution algorithm and use it to inform authority re-assignment for specific decisions.

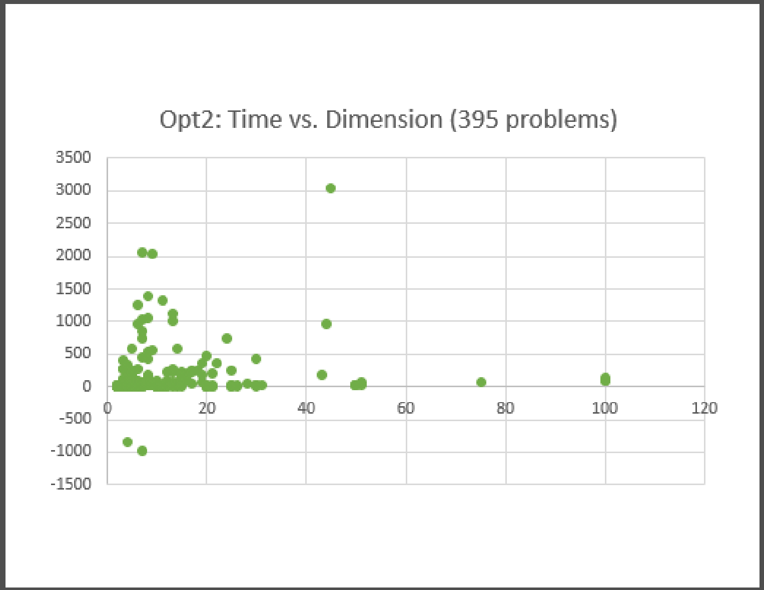
Example

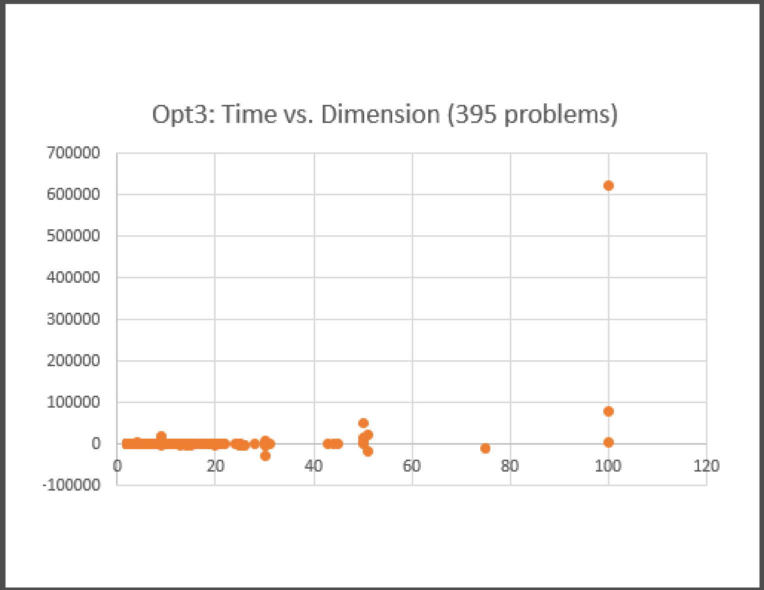
- Test set: 395 unconstrained and constrained problems [Hock and Schittkowski]
- Simulated Decision Makers
  - Opt1 (a feasible directions code)
  - Opt2 (a Kreisselmeier–Steinhauser code)
  - Opt3 (a sequential least squares code)

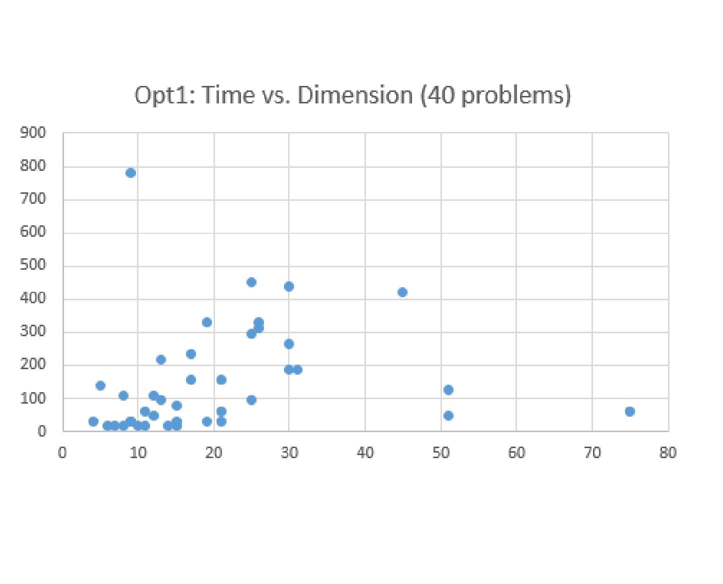


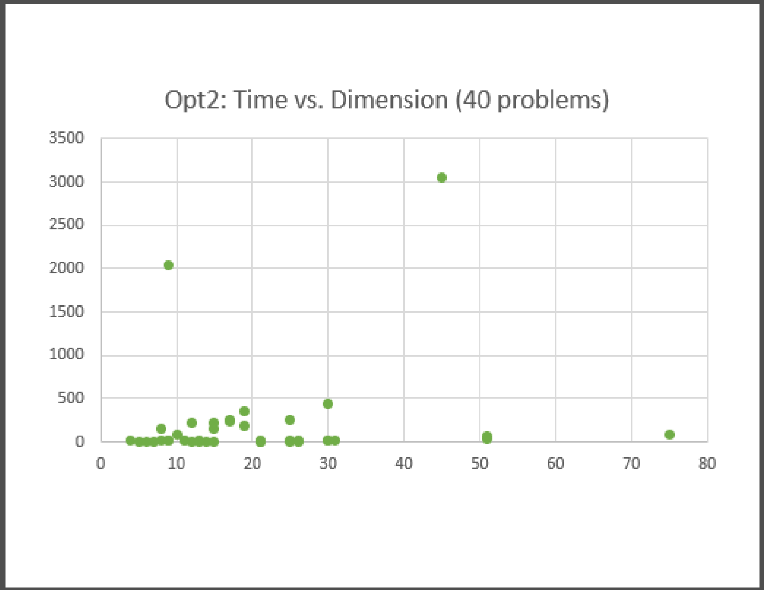
Decision-makers Performance

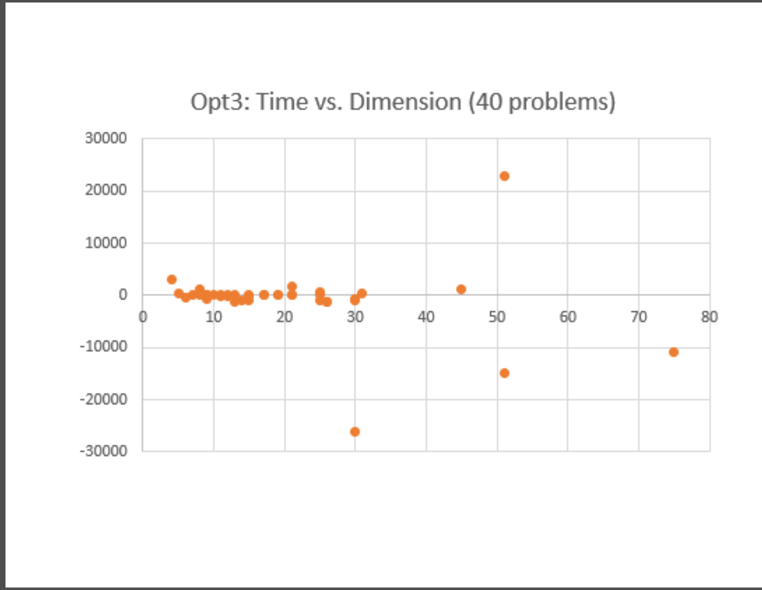












Relative Trustworthiness

- Simulated Decision Makers
  - Opt1
    - Declared success for all 395 problems.
    - Finished with violated constraints for 77 problems.
  - Opt2
    - Declared failure twice due to exceeding maximum number of iterations.
    - Finished with violated constraints for 39 problems.
  - Opt3
    - Declared failure when violated constraints for 32 problems.
    - Declared failure twice due to exceeding maximum number of iterations.

Relative Trustworthiness, cont.

- Simulated Decision Makers
  - Which to trust?
    - If “self-awareness” has the highest priority, then Opt3.
    - If never “stalling” has the highest priority, then Opt1.
  - In the works
    - Refined analysis of performance trends:
      - While computational complexity for arbitrary NLP is unpredictable, preliminary analysis shows trends related to function form (non-convexity, non-linearity).
      - Complexity modeling for problems that differ by dimension alone (e.g., in *ab initio* traffic modeling) appear to be more amenable to detection of performance trends.
    - Testing of multilevel algorithm for acceptance of decisions.
    - Testing of multiobjective formulation via non-antagonistic game theory [Germeyer, 1986].

N.B. Decisions from untrustworthy decision-makes must be accepted in the absence of alternatives and non-action.

Concluding Remarks

- Data collection via simulation-based and physical experimentation serves to build complexity models for environments of interest and agents' abilities to solve problems.
- A "look-ahead" into complexity parameters and the resulting estimate of complexity (tractability, quality of solutions, and other objectives) informs reconfiguration of the system or re-assignment of decision-makers until complexity estimates change again.
    - Re-assignment depends on context and problem dimensions.
- The approach pre-conditions the system to minimize the chances of losing solvability.

N.B. In H-M teams, while authority for a specific problem solution may be transferred to an M agent, continued participation of H agents is likely beneficial.

Acknowledgments: The author thanks the NASA LaRC CIF/IRAD Program for supporting this work and Greg Wrenn of AMA for generating data.